

[0012] Different calibrations may be used for different categories. For example, the calibration is for a histological subtype for the patient.

[0013] In a second aspect, a medical imaging system is provided for therapy decision support. A medical imager is configured to scan a patient. An image processor is configured to predict a result of therapy for the patient in response to input of scan data from the scan to a multi-task trained network. The image processor is configured to estimate a dose for the therapy from a regression relating the dose, a time-to-event, and the result. The dose is estimated from the regression so that the result is below a threshold probability of failure at a given value of the time-to-event. A display is configured to display the predicted result.

[0014] In one embodiment, the medical imager is a computed tomography imager where the multi-task trained network was trained using a first loss for image features based on handcrafted radiomics and using a second loss for outcome.

[0015] In another embodiment, the regression is a calibration from a cohort used to train the multi-task trained network. In other embodiments, the regression is a nomogram relating the dose, the time-to-event, and the result. The dose may be modeled as a continuous variable in the regression. The regression may be based on estimation of a cumulative incidence function.

[0016] In an embodiment, the threshold probability is 5%. Other values may be used to estimate the dose to result in the probability of recurrence being below the threshold. In other embodiments, the image processor is configured to estimate the dose as providing the result in the given value for the time-to-event, such as in 12 or 24 months.

[0017] The regression may be for all patients. Alternatively, the regression is specific to a given histological subtype.

[0018] Any one or more of the concepts described above may be used alone or in combination with each other and/or aspects in the parent application. The aspects or concepts described for one embodiment may be used in other embodiments or aspects. The aspects or concepts described for a method or system may be used in others of a system, method, or non-transitory computer readable storage medium.

[0019] These and other aspects, features and advantages will become apparent from the following detailed description of preferred embodiments, which is to be read in connection with the accompanying drawings. The present invention is defined by the following claims, and nothing in this section should be taken as a limitation on those claims. Further aspects and advantages of the invention are discussed below in conjunction with the preferred embodiments and may be later claimed independently or in combination.

BRIEF DESCRIPTION OF THE DRAWINGS

[0020] The components and the figures are not necessarily to scale, emphasis instead being placed upon illustrating the principles of the embodiments. Moreover, in the figures, like reference numerals designate corresponding parts throughout the different views.

[0021] FIG. 1 illustrates an example of machine training a decision support system;

[0022] FIG. 2 illustrates another example of machine training a decision support system;

[0023] FIG. 3 is a flow chart diagram of one embodiment of a method for machine training decision support in a medical therapy system;

[0024] FIG. 4 is a flow chart diagram of one embodiment of a method for decision support in a medical therapy system;

[0025] FIG. 5 shows an example machine-learning network for training using radiomic feature loss with a more commonly available ground truth than outcome;

[0026] FIG. 6 shows another example machine-learning network for training using segmentation loss with the more commonly available ground truth than outcome;

[0027] FIG. 7 shows an example machine-training architecture for a multi-task generator;

[0028] FIG. 8 shows another example machine-training architecture for a multi-task generator;

[0029] FIG. 9 shows an example of use of two losses in training of a multi-task generator;

[0030] FIG. 10 shows another example of use of two losses in training a multi-task generator;

[0031] FIG. 11 is one embodiment of an arrangement using both prediction of outcome and clustering in decision support;

[0032] FIG. 12 show a comparison of example outputs of survival using handcrafted radiomics and a multi-task generator;

[0033] FIG. 13 is a block diagram of one embodiment of a system for therapy decision support;

[0034] FIG. 14 is a flow chart diagram of one embodiment of a method for decision support in a medical therapy system, where determination of individualized dose is provided based on the outcome generated in the embodiment of FIG. 4;

[0035] FIG. 15 illustrates an example relationship between radiation dose, treatment failure, and score output by a machine-learned network; and

[0036] FIG. 16 shows comparison in examples of calibration curves relative to observed calibration curves.

DETAILED DESCRIPTION OF EMBODIMENTS

[0037] An imaging-based artificial intelligence provides for patient stratification and/or radiotherapy response prediction. This radiotherapy decision support may be based on pre-treatment CT or other modality scans. The therapy outcome may be predicted based on imaging and/or non-imaging data, providing physician decision assistance.

[0038] FIGS. 1-12 are directed to decision support using a machine-learned model. FIGS. 14-16 are directed to individualizing dose based, in part, on the image information as provided by the machine-learned model of the decision support, a low threshold of probability of failure, and a time-to-event.

[0039] FIG. 1 shows one embodiment of a decision support system for producing prognostic signatures of the therapy from radiological imaging data. The signature is patient information or features from imaging data of the medical image. The medical image is preprocessed, such as scaled, normalized, and/or segmented for tumors or regions including tumors. Different from traditional radiomic features that are usually handcrafted, deep-learning-based radiomic features that are completely data-driven are to be used. The handcrafted radiomics are used as ground truth as these features may be created from any image, allowing for unsupervised learning or ground truth unlabeled for the